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Research Article

Technoeconomic Distribution Network Planning Using Smart Grid Techniques with Evolutionary Self-Healing Network States

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The transition to a secure low-carbon system is raising a set of uncertainties when planning the path to a reliable decarbonised supply. The electricity sector is committing large investments in the transmission and distribution sector upon 2050 in order to ensure grid resilience. The cost and limited flexibility of traditional approaches to 11 kV network reinforcement threaten to constrain the uptake of low-carbon technologies. This paper investigates the suitability and cost-effectiveness of smart grid techniques along with traditional reinforcements for the 11 kV electricity distribution network, in order to analyse expected investments up to 2050 under different DECC demand scenarios. The evaluation of asset planning is based on an area of study in Milton Keynes (East Midlands, United Kingdom), being composed of six 11 kV primaries. To undertake this, the analysis used a revolutionary new model tool for electricity distribution network planning, called scenario investment model (SIM). Comprehensive comparisons of short- and long-term evolutionary investment planning strategies are presented. The work helps electricity network operators to visualise and design operational planning investments providing bottom-up decision support.

1. Introduction

Distribution networks are a key enabler for a low-carbon future. In the UK, distribution network operators (DNOs) are entering a period of significant changes due to UK energy targets up to 2050 [1]. By 2020, it is expected that 15% of its total demand will be from renewable energy sources with a 20% reduction in greenhouse gas emissions and, moreover, 80% reduction in greenhouse gas emissions by 2050. The challenges presented by the transition to a low-carbon economy will directly impact the electricity distribution network.

As for an increasing connection of distributed generators and electrification of heat and transport, new approaches to design, construct, and operate networks will be required [2]. A more active management of local distribution networks, interconnections, storage, or flexibility services are some of the strategic propositions that will maximise the full potential of the digital network revolution. In that sense, the UK National Infrastructure Commission, the UK regulator, OFGEM, and the Department of Business, Energy and Industrial Strategy (BEIS) are contributing to the smart, flexible energy system debate [3].

In 2010, OFGEM introduced RIIO, namely, setting revenue using incentives to deliver innovation and outputs [4]. This new performance-based pricing framework sought to make network operators more consumer-centric encouraging longer-term thinking, greater innovation, and more efficient delivery.

The RIIO framework has been applied to both gas and electricity transmission and distribution networks. The current price control (called “RIIO-1”) is the first generation

(2015–2023) of controls under this new framework. As we look forward towards the discussion of defining the price control for RIIO-2 (2023–2031), we have to take account of the dramatic changes and the increased complexity that are underway in the energy sector, as well as the experience and lessons learned, from RIIO-ED1 by DNOs.

In response to these challenges, DNOs are evaluating the performance of novel intervention techniques along with traditional reinforcements for future network planning [5–7]. Furthermore, the deployment of these novel techniques is expected to improve the quality of service [8]. The rising number of stakeholders in the electricity value chain increases the complexity for asset planning. Besides the number of decision makers, the energy sector is facing a data revolution, and therefore, utilities of the future must include in their planning capabilities the implementation of information and communication technologies (ICTs).

Most network modelling tools, such as IPSA Power, ETAP, or DINIS [9–11], perform power flow analysis and look after overloads and stress points of the network. Their approach can be considered static, in the sense that they evaluate an instantaneous view of the network at a certain given time. However, dynamic modelling like the ones implemented within the SIM [12] extends those static approaches making a series of evaluation runs, adjusting future network states (configuration of the network) to previous fixed states where the grid needed an intervention across its topology.

The novel techniques under study in this research are classified as engineering techniques: automatic load transfer (ALT), dynamic asset rating (DAR) for cables and transformers, meshed networks, and energy storage, and commercial techniques: distributed generation (DG) and demand side management (DSM). Traditional reinforcements (TRAD) are modelled as follows: transformer replacement or addition; cable or overhead line (OHL) replacement; transfer load to adjacent feeder; and installation of new feeder [13]. In addition, the assets considered to be fixed during this assessment are the cables and transformers of the local 11 kV network.

This study is populated with the data from the FALCON (Flexible Approaches to Low Carbon Optimised Networks) project trials, using a section of Western Power Distribution (WPD) in Milton Keynes area, composed of six 11 kV primaries. In contrast with the parametric top-down representation embedded in the transform model [14], the SIM aims at creating long-term strategic investment plans. This study will deliver insights and scalability of these novel interventions for asset planning of the UK distribution power networks.

There are a number of previous notable projects that address the uncertainty around the integration of low carbon and low-carbon technologies into the distribution grid [15–18]. The smart distribution network operation for maximising the integration of renewable generation project [19] performs the optimisation of network operation modes and reinforcement planning in the presence of renewable generation. The OFGEM smart grid forum work stream 3, which later became the EA technology transform model [14], is a parametric representation of the electricity distribution network that aimed at creating long-term strategic investment plans [20]. It is important to note that there are certain limitations in transform that are characteristic to all parametric models. The operating characteristics of devices and their relationship to other technologies require extensive calibration to produce a qualified answer. To some extent, the limitations of transform were addressed by smart grid forum work stream 7 [21], which took four of transform's parametric representations of typical distribution networks and converted them into nodal network models. Other examples include the energy system catapult energy path model, which targets local energy systems [22], and the Comillas University reference network model (RNM) [23], which is a large-scale distribution network planning tools that can create optimal networks.

Despite the differences in their respective approaches, the aforementioned models and software tools share some common limitations [24]. They have limited ability to capture emerging behaviour arising from the simultaneous application of multiple low-carbon and smart technologies to the electricity distribution network. Likewise, it is complex to add new technologies into the mix, due to either the lack of automatic application of smart techniques or, as in the case with transform, the parametric approach which needs information about the way different technologies compete with each other, which is difficult to obtain. And finally, no decision support for a particular piece of distribution network can be provided because of either lack of automation or the parametric nature of the model. The following sections introduce and describe the smart techniques and the novel technoeconomic approach for performing dynamic network modelling in distribution networks and analysis in the presence of multiple smart grid techniques. It uses nodal network modelling to capture the emerging behaviour and create localised network development plans.

2. Overview of Techniques

2.1. Technique 1: Dynamic Asset Rating. The heating effect of current passing through a metal restricts the capacity of all transformers, overhead conductors, and cables on a distribution network represented in Figure 1. This restriction is based on the maximum temperature on a critical component within the asset. Therefore, each asset will have a finite current-carrying capacity rating based on assumed values of external conditions which affect thermal buildup, i.e., wind speed, ambient temperature, soil, and humidity. As the assets in general do not have temperature monitoring, the assumed values of the external conditions used in these calculations have as a basis a statistically low level of the risk of the asset exceeding its critical temperature. By more accurately monitoring metrological conditions and modelling asset ratings in real time, the capacity of the asset can be increased while keeping the risk of exceeding the critical temperature to a minimum. Further models and algorithms will be developed as part of this second implementation to cater for the increased information available.

In addition, many assets have a thermal capacity, such that it takes time for the asset to raise its temperature

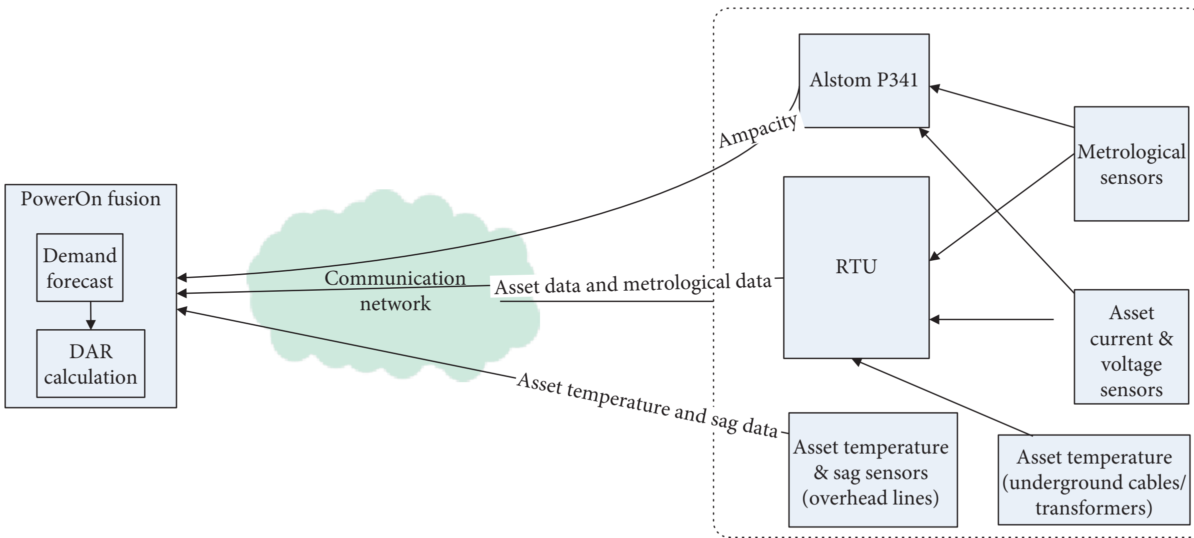

Figure 1: DAR trial schematic.

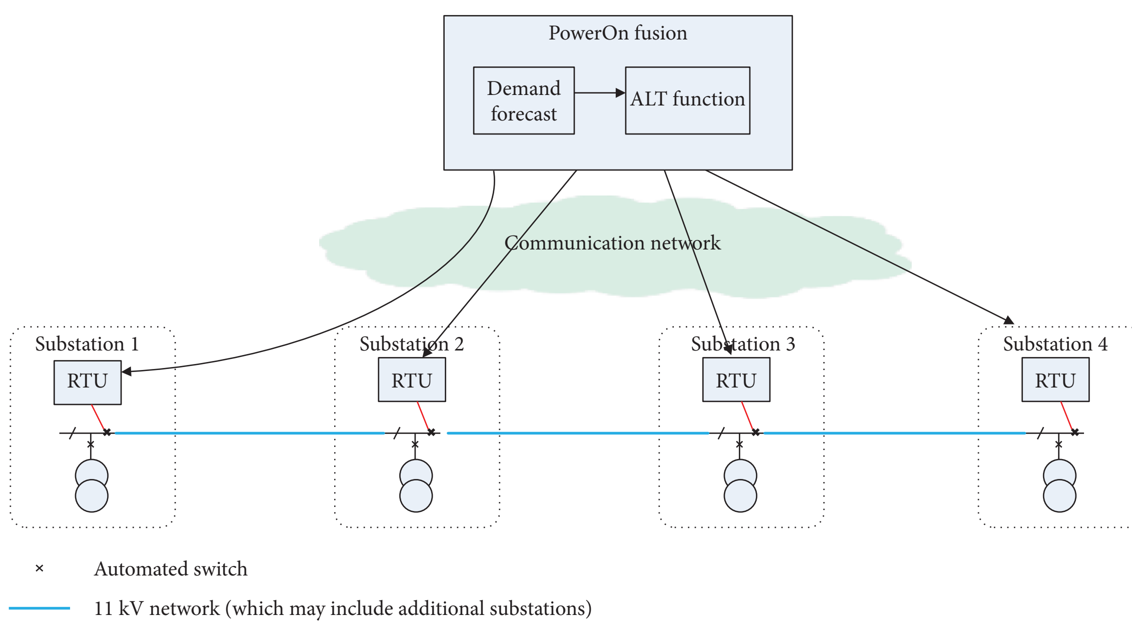

Figure 2: ALT trial schematic.

(i.e., an increase in the current passing through the asset will not cause a step change in the temperature of the asset). Such assets typically have short-term current ratings which are significantly greater than their continuous current rating. These short-term ratings are based on specific current-carrying curves. By being able to forecast the actual current-carrying curves, the asset ratings can be further refined such that an even greater short-term current can be supported. Transformers and underground cables have significant thermal capacity that can utilise this method whereas overhead line circuits do not have significant thermal capacity.

2.2. Technique 2: Automated Load Transfer. Consumers of electricity on the network use energy at different rates at different times of the day, and by actively managing the network connectivity, the loads across connected feeders can be evenly balanced. Rather than the position of normal switching open points being determined for average network conditions, the positions can be changed automatically by the network management system to a more optimum location based on a number of factors such as security, voltage drop, capacity utilisation, and load forecasts as displayed in Figure 2.

2.3. Technique 3: Meshed Networks. This technique represents the process by which circuit breakers on the network are switched in order to feed loads from multiple locations. This approach fundamentally allows the load on each feeder

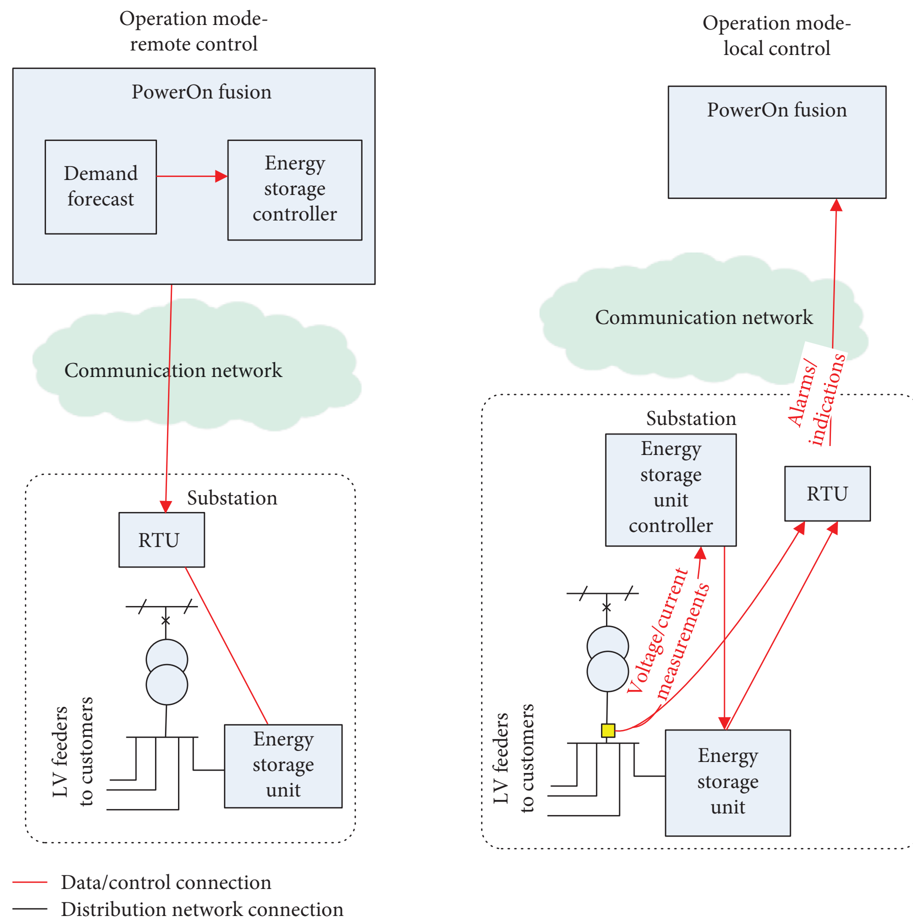

Figure 3: Storage trial representation.

in a meshed circuit to deviate according to the routine variations in the connected load, without the need for pre-existing analysis and changes to switch states.

However, simply closing normal open points (NOPs) exposes more connected customers to supply interruption following a network fault. Therefore, any planned closure of open points for long-term operation is routinely accompanied by the installation of along-the-feeder fault sensing and interruption equipment (protection relays and circuit breakers). The installation of along-the-feeder protection devices restores and potentially reduces the probability of customer interruption under fault conditions with mesh operations.

The aim of trialing this technique was to operate the designated 11 kV networks with parallel feeding arrangements, protective device-driven autosectioning zones, while exploring: potential impacts, both benefits and trade-offs, that could be derived from parallel feeder configurations; and potential impact, both benefits and constraints of operation with autosectioning zones balanced against time/effort and cost.

2.4. Technique 4: Storage. Energy demand in an 11 kV feeder tends to occur in peaks and troughs throughout a 24-hour cycle. The current supplying capacity of a feeder is limited to the current-carrying capability of the smallest cable or conductor in the circuit, and these usually decrease in cross-sectional area size further away from the primary they are located. This is acceptable when the load is spread evenly across a circuit, but when the load occurs unevenly, then the utilisation factor of the assets will also be uneven. By introducing energy storage devices on the network (Figure 3), they can feed out onto the system at peak demands and recharge during times of low demand, thus deferring the need to replace existing assets.

2.5. Technique 5: Distributed Generation Control. A number of industrial and commercial customers have their own on-site generation, and this number is likely to increase with the transition to a low-carbon economy. In some cases, this may be uncontrollable renewable generation (wind or solar) but the majority is in the form of either standby generators or controllable plants such as biomass, refuse incinerators, or combined heat and power (CHP) plants. If customers with controllable distributed generation can be incentivised to accept instruction from a DNO to increase or decrease generation, this can be used to reduce or increase site demand and/or provide or remove supply from the grid as a means of rectifying network problems.

2.6. Technique 6: Demand Side Management. Similar to distributed generation, DSM involves putting in place

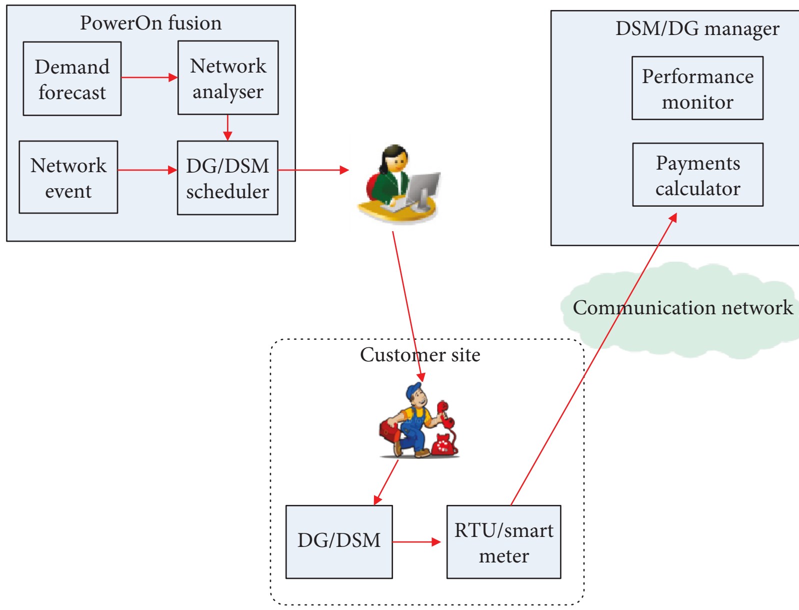

FIGURE 4: Commercial trials representation: DG/DSM.

commercial agreements between the DNO and industrial and commercial customers who have the ability to control appreciable amounts of load in a relatively short period of time. We expect demand side response to be in two forms using the representation in Figure 4:

(i) To reduce the impact of predicted peak loads

(ii) To respond to an unplanned event, such as a fault

Demand side response actions can be used by the DNO to enable a change in behaviour by a customer site in response to an explicit signal triggering a preagreed action. The action should be the interruption of a customer's internal electricity-consuming processes, either to avoid or, more likely, to defer these to a later time. Its metrics: capacity/delta reduction, duration/frequency, and OPEX, are detailed in [13].

3. Methodology

To undertake the analysis of the aforementioned techniques, a revolutionary new software tool for electricity distribution network planning, called the scenario investment model (SIM), is used. Results from evaluations using the SIM are obtained through a series of experiments that modelled the network evolution under different demand scenarios, presented in Table 1, at short- (2015–2023) and long-term lookahead (2015–2050) to assist decision-makers in future power network planning.

Currently, electricity distribution networks have been planned with typically linear load growths of up to 1% per annum. The expected increase in low-carbon technologies will have a significant effect on the electricity demands on the network which may have significant rapid sporadic increases in the electricity demand on the 11 kV networks [25]. In addition, the daily electricity load shapes may be also altered significantly. The networks will need to be upgraded, and systems are being able to evolve and cope with new demand profiles.

TABLE 1: Demand scenarios.

Demand scenarios	Fuel efficiency	Low-carbon heat	Wall insulation
DECC1	Medium	High	High
DECC2	High	Medium	High
DECC3	High	High	Low
DECC4	Low	Low	Medium

There had been identified two main streams of work to consider the use of the innovative techniques, namely, strategic and tactical planning and Design, Build, and Operation. The strategic and tactical planning stream will consider the network planning roles while the design and operation stream will consider design, build, and operation roles. In Figure 5, the smart grid planning framework diagram presents the key elements of each stream which are displayed with their main interactions.

In order to leverage the capability of existing network analysis tools which are already extensively used by electricity network operators, the SIM is separated into two main packages: a network modelling tool which primarily performs the technical assessment of the application of the techniques and the SIM harness which manages the overall process and perform the economic assessment and reporting functions.

Demand data modelling has been based on a bottom-up approach. The methods used provide an estimate of demand for each half-hour at each secondary substation for 18 different season-day types [12].

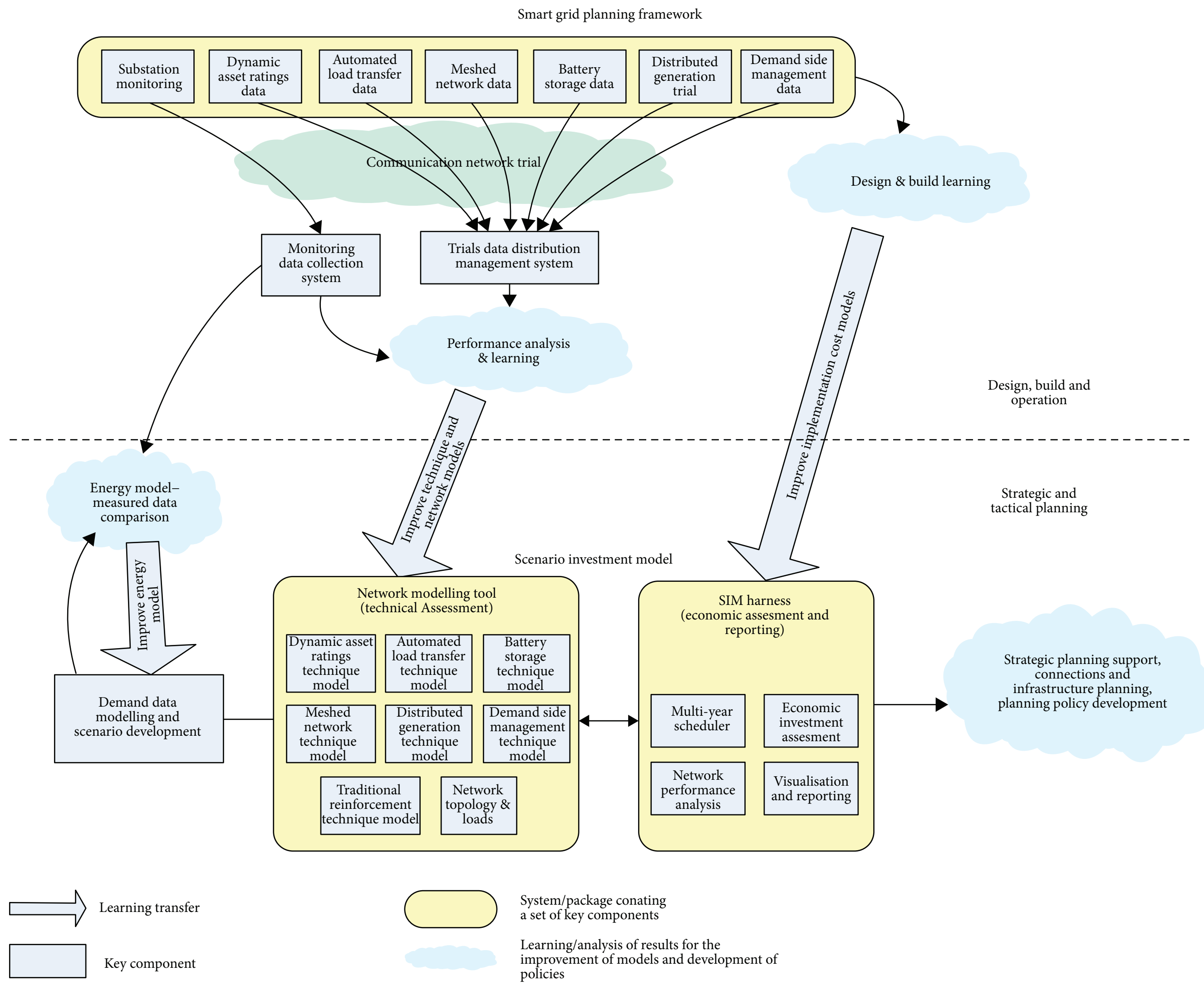

Figure 5: Smart grid planning framework diagram.

The research objective is settled to prove the suitability of the six novel smart interventions presented in Section 2 and, along with the traditional reinforcements, provide an evolutionary planning insight for future power networks. To undertake this study, specific experiments were selected for a certain power trial network under different demand scenarios and evaluation periods, assessing smart techniques along with traditional reinforcements. The approach involved running a set of experiments using the SIM for the six 11 kV primaries in the FALCON trial area.

3.1. SIM Support Algorithms. The essence of the SIM approach is its ability to take a network configuration and corresponding load profiles in a particular year (termed as initial network state), perform power flow and reliability analysis, and create derivative network states in a process known as "network state expansion." The expansion happens either by transitioning to the following year for network states without any failures or by applying intervention techniques to resolve network issues. With each new network state created, the SIM, therefore, is faced with a decision as to which network state from the execution history to expand next. The expansion can be guided by simple depth first or breadth first algorithms, which are implemented in the SIM for verification purposes. The depth-first algorithm always selects the newest, i.e., the most recently created network state that is not fully expanded for expansion, while the breadth-first algorithm always selects the oldest network state. However, those simple heuristics are inadequate for any practical use beyond simple test cases due to the size of the search space obtained by permuting all possible interventions over a number of years. To perform intelligent exploration of the search space, the SIM uses a heuristic approach that is based on an A* algorithm [26, 27].

The baseline A* algorithm aims at finding the least-cost path through the search space. As A* traverses the search space, it builds a tree of partial paths. The leaf nodes of this

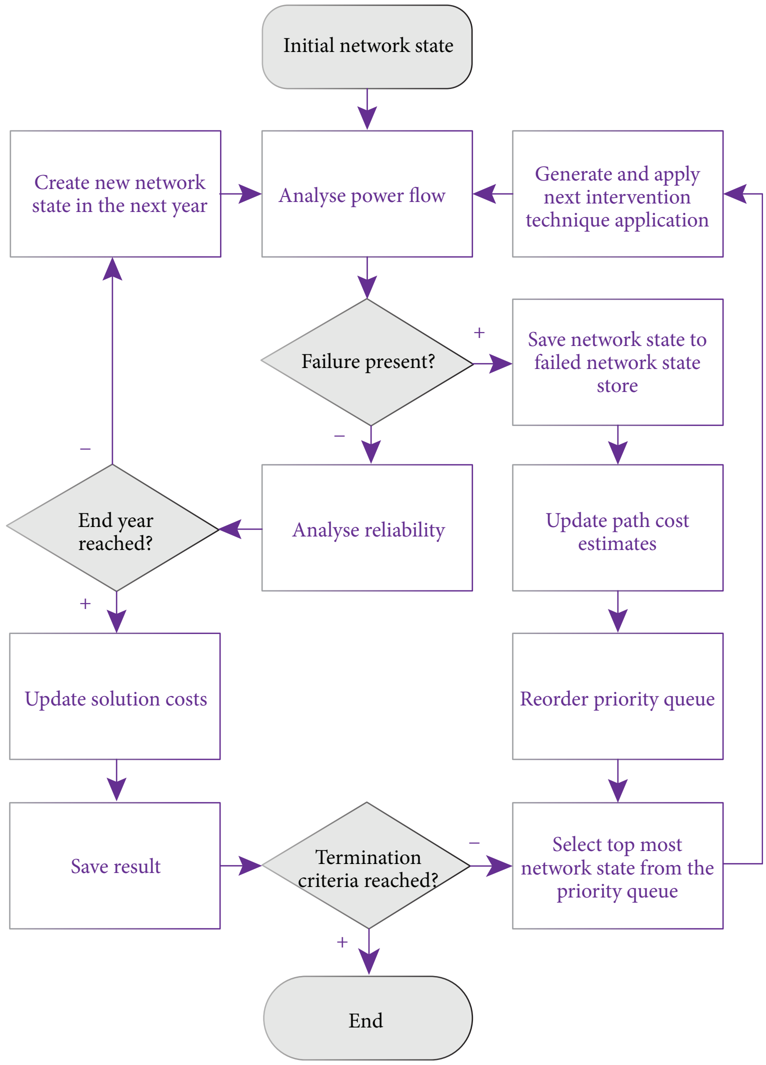

Figure 6: SIM evaluation flowchart.

tree (failed network states) are stored in a priority queue that is ordered using a cost function:

$$f(x) = g(x) + h(x), \quad (1)$$

where $h(x)$ is a heuristic estimate of the path cost to reach the goal and $g(x)$ is the distance travelled from the initial node.

The SIM selects network states from the priority queue to apply intervention techniques, one application at a time. Deployment of a technique produces a new network state, for which a power flow analysis is performed in intact and all $n-1$ (contingency) network operation modes. If all the failures are resolved, a reliability analysis comprising customer minutes lost (CML), customer interruptions (CI), losses, and fault level studies is performed. A new network state is subsequently created in the next year of evaluation, or if it is already the last year of evaluation, the costs of interventions are calculated and the network state together with all its expansion history is saved to the result store as a new result. The evaluation is terminated (Figure 6) when criteria such as the number of results, number of network state evaluations, or run time are reached. As noted, previously, A* uses a combination of distance travelled so far and a heuristic estimate of the distance to reach the endpoint.

In SIM case, this corresponds to $g(x)$ being the total expenditures (TOTEX) incurred so far and $h(x)$ being a heuristic estimate of TOTEX to reach the end year of the experiment. TOTEX, also referred to as the total expenditure, comprises implementation costs (CAPEX) that occur only once when an intervention is applied to the network, operation costs (OPEX) that refer to an ongoing expense of operating an asset or a scheme along with asset life degradation, and metric costs that include incentive payments for losses, fault levels, and network reliability. Referring to (2), the $g(x)$ for a network state x_i in year i is defined as

$$g(x_i) = (c_i + o_i) + \sum_{j=1}^{j-1} (c_j + o_j + m_j), \quad (2)$$

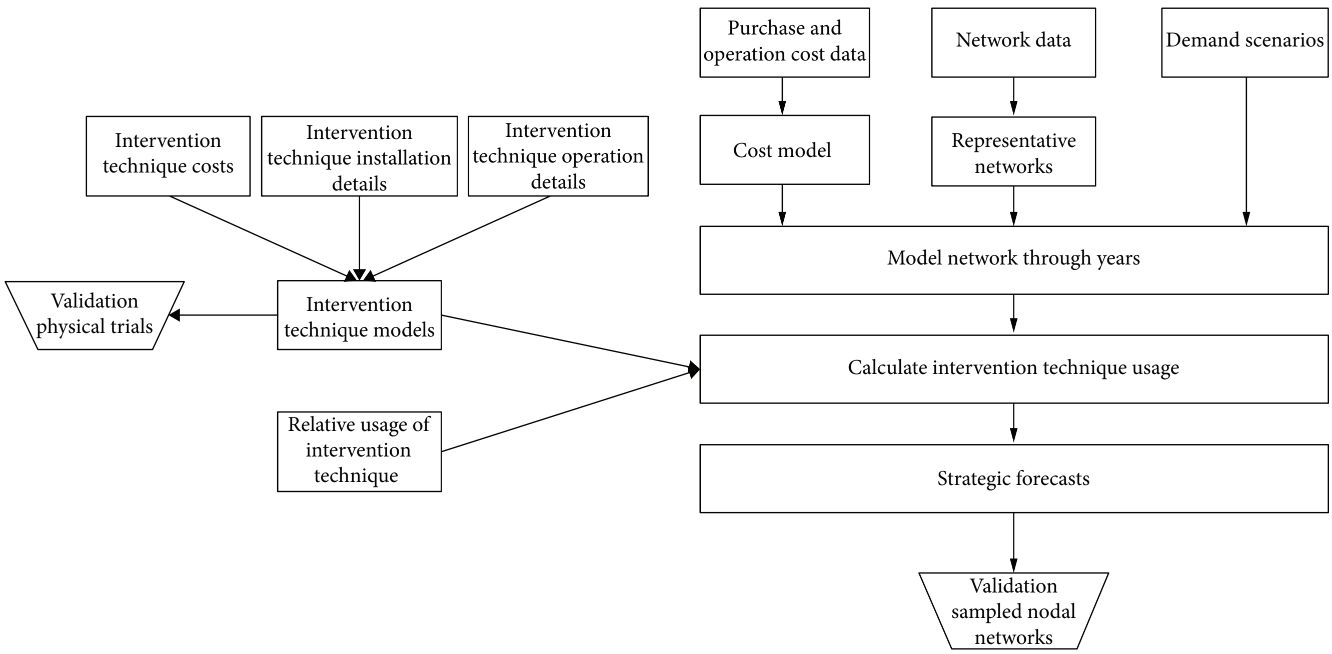

Figure 7: Top-down conceptualisation of evolutionary power networks planning.

where c_i is CAPEX in the current year; o_i is OPEX in the current year; and c_j, o_j, and m_j are CAPEX, OPEX, and metrics costs, respectively, of the ancestor network state with no issues in year j. The heuristic estimate $h(x)$ of the cost to reach the end year is given by

$$h(x_i) = (\bar{c}_{\mathrm{REM}i} + \bar{m}_i) + \sum_{k=i+1}^{n} (\bar{c}_k + \bar{o}_k + \bar{m}_k), \quad (3)$$

where $\bar{c}_{\mathrm{REM}i}$ is the average remaining CAPEX in the current year i; $\bar{m}_i$ is the average metric cost in this year; $\bar{c}_k$, $\bar{o}_k$, and $\bar{m}_k$ are the average CAPEX, OPEX, and metric costs, respectively, of the descendant network state in year k with no issues; and n is the end year of evaluation. Preseeded to a constant value, $\bar{c}_0$, the average CAPEX is updated each time a network state is expanded in a particular year; thus, the estimated costs of fixing all issues in a particular year progressively approach true average. Setting $\bar{c}_0$ to a value greater than 0 speeds up the expansion process; i.e., all interventions that cost less than $\bar{c}_0$ will result in new network states that are at the top of the priority queue. The business rationale is that DNOs are not that interested in optimizing interventions costing less than a certain threshold. The learned averages are propagated back to network states in the priority queue, thus updating their estimated effort and leading to the reordering of the queue, unlike the average CAPEX, average OPEX, and metrics costs which are assumed to be 0 for years with no network states. The average OPEX value for a year is obtained using

$$\bar{o} = j^T o_c \left(j^T j\right)^{-1}, \quad (4)$$

where j is a column vector of ones and $\bar{o}_c$ is an OPEX vector of compliant network states in that year. Likewise, the average metric cost is obtained according to

$$\bar{m} = j^T m_c \left(j^T j\right)^{-1}, \quad (5)$$

where j is a column vector of ones and $\bar{m}_c$ is a vector of the metric costs of compliant network states in that year.

3.2. Conceptualising Bottom-Up Evolutionary Planning. Model-driven engineering (MDE) uses analysis, construction, and development of frameworks to formulate metamodels. Those models are usually characterised using domain-specific modelling approaches [28], containing appropriate detail abstraction of particular domain through a specific metamodel. The use of metamodels requires therefore inputs from domain experts which can be used to generate aggregated or disaggregated models. Top-down and bottom-up are the conceptual definition of aggregated and disaggregated models [29]. These two modelling paradigms are frequently used to epitomise domain interactions among the operation of the energy system, the econometrics related, and the technical performance indicators [30].

From a bottom-up modelling approach [31, 32], the top-down perspective is a simplistic characterisation of how electrical power networks combine locational events and individual asset performance with high-level objectives like improving the CML of a certain congested area [33, 34]. From an engineering point of view, both are still valid since outputs and strategic forecast are produced in both. How those outcomes are calculated, validated, and transformed to strategy is presented in Figure 7 (top-down) and Figure 8 (bottom-up).

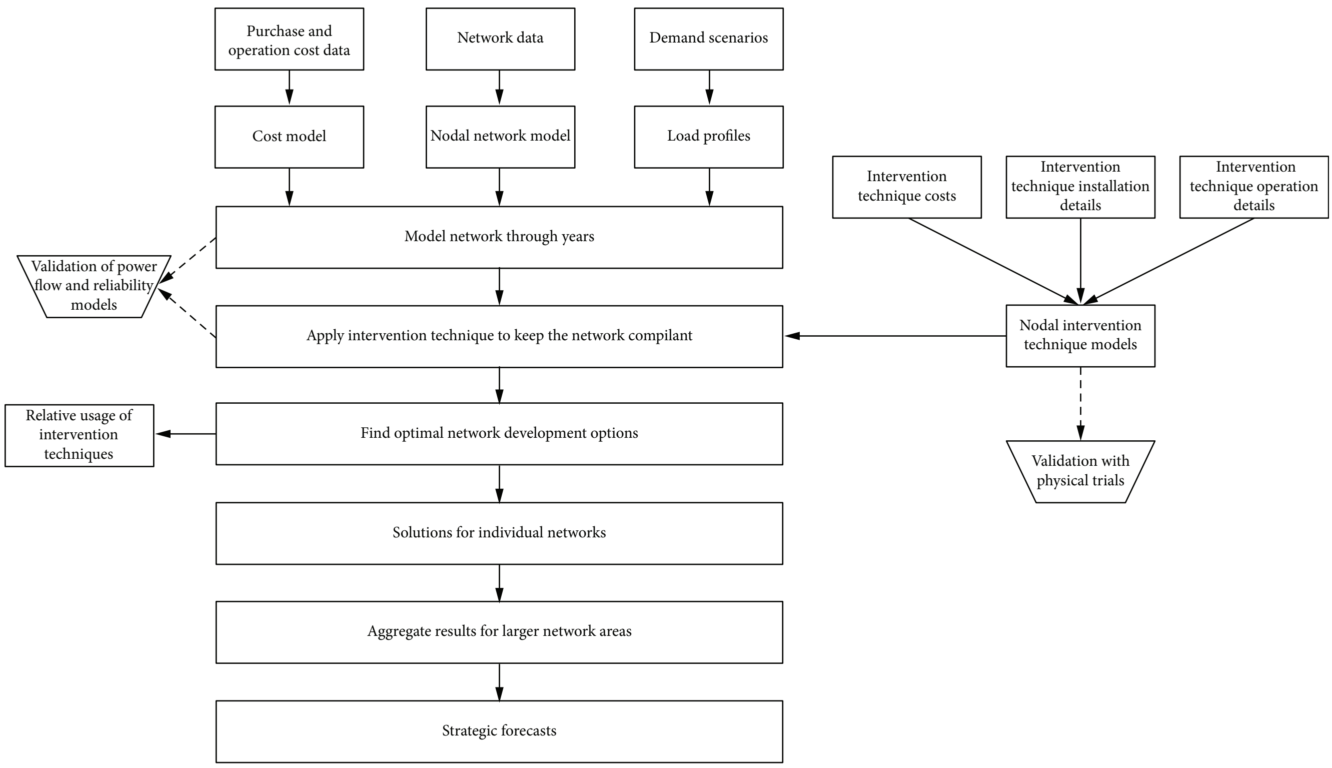

Figure 8: Bottom-up conceptualisation of evolutionary power networks planning.

The ability of bottom-up to capture discrete locational impacts of technologies on the system and their disaggregated costs is triggering the following subsections. Trade-off methodologies are needed for planning evolutionary power systems where observing disaggregated result strategic forecasts are to be produced. These methodologies need to be interactive in the sense that starting from an initial state and after a testing or learning phase, the network is able to accommodate techniques that have improved the system, providing an exploratory set of solutions that can be expanded or discarded as the model evolves through time.

3.3. Experiment Characterisation. To illustrate the processing of the methodology adopted, we consider a typical network scenario tree created by the tool that consists of failed (red) and compliant (green) network states in different years of evaluation. The SIM starts with a single network state in the first year of evaluation. Every year, the network is evaluated for compliance in intact and $n-1$ contingency operation modes. If failures are detected, the SIM applies intervention techniques described in Section 2 to create network patches that resolve the failures. Each application of an intervention technique creates a new network state. The tool has to resolve all issues in the network before transitioning into the next year. DNO planners usually run power flow studies with a single fixed load pattern. In contrast, the SIM checks each network state for compliance under 18 characteristic day load scenarios each comprising of 48 half-hour settlement periods. All studies are performed under intact and $n-1$ contingency network operation modes. The SIM calculates patch costs using cost drivers returned by the network modelling tool. The cost driver describes a network intervention and consists of two parts, namely, the patch key and the scaling. The patch key identifies the nature of the modification of the network performed (removal or addition of an asset and the type of the asset). Scaling data is relevant only to patches that can be installed in multiples of one, such as cable upgrades and additional transformer installation. Scaling data structure provides a list of multipliers to the base cost data available in the SIM database. In case of cable upgrade or replacement, it enables the SIM to correctly estimate full installation costs from per unit of length values. Finally, for postprocessing analysis, the SIM also returns a list of failures by asset. It was identified by DNO planners as indispensable features to help validate the system and correlate the expansion trees to the actual assets on the network diagram. The failure detail table contains asset ID and description alongside information about the number of failures in intact and $n-1$ operating modes as well as absolute and per unit thermal and voltage failure magnitude.

3.4. Case Characterisation. Two set of experiments were performed for this study, one for comparing short-term evaluation period for RIIO-ED1 (2015–2023) where the RIIO-ED1 investment planning has been stylised and a longer planning period for RIIO-ED1 to RIIO-ED4, from 2015 up to 2047. The other set aimed at evaluating different DECC demand scenarios. Experiments evaluated two demand scenarios: DECC2 and DECC4. DECC4 represents, as displayed in Table 1, the slow-progression scenario, and

DECC2 is with DECC3 the most challenging scenario in terms of electrification and low-carbon technology integration. The procedure to run the experiments in the SIM is shown in Figure 6. The inputs to be sent to the SIM are detailed in Figure 5, the selected network, techniques, evaluation period, demand scenario, and cost model, whereas the outputs of the SIM we obtain are techniques used, failures solved, assets fixed, and electrical performance indicators. The SIM address mentioned outputs for long-term planning reinforcements, to optimise investment asset planning resolving network constraints. The performance criteria evaluated were capital expenditures (CAPEX), operating expenditures (OPEX), utilisation of assets, CMLs, CIs, and losses. These parameter values are delivered by the SIM after each simulation. In order to look for the optimal solution among the feasible solution pathways, the SIM allows a granularity study of each network state.

4. Results

This section presents the assessment of the six smart grid interventions along with traditional reinforcements in the trial area, compounded by six 11 kV primaries in Milton Keynes, UK, for two different evaluation periods, DECC2 and DECC4. Subsection 4.1 introduces the results for the 2015–2023 period as short-term planning, and Subsection 4.2 presents the results for a long-term evaluation period, 2015–2047.

4.1. Short-Term Planning. This section presents the assessment of the six smart grid interventions along with traditional reinforcements in the trial area, compounded by six 11 kV primaries in Milton Keynes, UK, for two different demand scenarios, DECC2 and DECC4.

4.1.1. DECC4, 2015–2023. Figure 9 shows the trends of CAPEX and OPEX. Note that in the year 2015, there is a CAPEX's peak due to the application of more techniques and OPEX increments over time from 2017 to 2023.

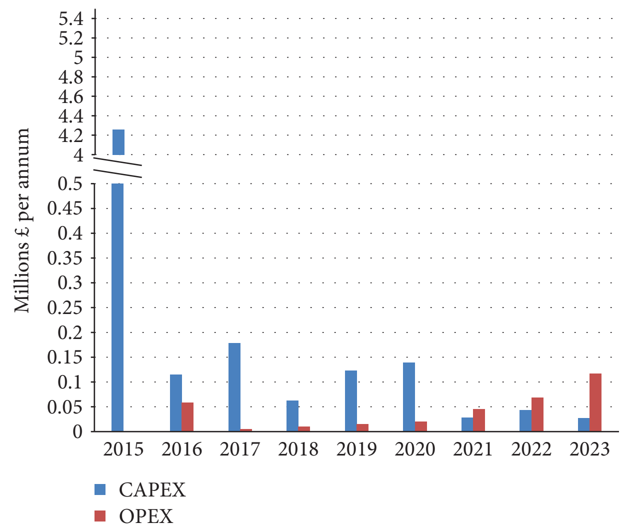

Figure 9: CAPEX and OPEX; DECC4, 2015–2023.

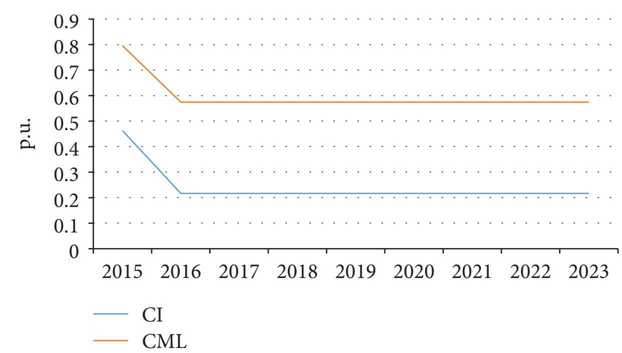

Figure 10: CML and CI; DECC4, 2015–2023.

Despite the investment, the increase is compensated by a benefit in the electricity distribution network, with a reduction in CML and CI as shown in Figure 10.

The summary of the proportion of installations required during this evaluation period and by capital expenditures per technique is presented in Table 2 for both DECC scenarios.

The average yearly price of each technique implemented to fix a network state is key for future decision-making considerations.

Figure 11 displays the average price of each technique disaggregated by CAPEX and OPEX.

Performance indicators are key parameters for future decision-making within electricity distribution planning as quantifiers due to their influence on the quality of service.

Therefore, as shown in Figure 12, the only smart technique used in combination with traditional reinforcements in this scenario and evaluation period that slightly influence slightly CML and CI is meshed networks.

4.1.2. DECC2, 2015–2023. Figure 13 plots the trend of CAPEX and OPEX over the evaluation period. It is important to highlight that there is a CAPEX peak in 2015, due to an increase of techniques applied in this period.

This CAPEX increment produces a benefit in terms of CML and CI, as observed in Figure 14.

The distribution of techniques applied and capital expenditures per technique are shown in Table 2. The average price of each technique implementation in this demand scenario for this evaluation period is shown in Figure 15.

As displayed in Figure 12 for DECC4's simulation, the only smart grid technique that improves the quality of service is the meshed network. In Figure 16, the contribution of smart techniques on CML and CI for DECC2 demand evaluation is captured.

4.1.3. Comparison between DECC2 and DECC4 for 2015–2023. The results presented may facilitate improvements in electricity distribution network operations and planning resulting in better-informed decision-making when upgrading current electricity distribution networks. The assessment of the six smart grid techniques discovered that only three of them were selected as part of optimal

Table 2: Number of interventions and CAPEX involved; DECC4 and DECC2, 2015–2023.

Technique	DECC4 Proportion of interventions (%)	DECC4 CAPEX (%)	DECC2 Proportion of interventions (%)	DECC2 CAPEX (%)
DAR-cable	15%	2%	14%	2%
DAR-transformer	7%	1%	5%	1%
ALT	0%	0%	0%	0%
Mesh	3%	1%	4%	1%
Batteries	0%	0%	0%	0%
DSM	0%	0%	0%	0%
DG	0%	0%	0%	0%
TRAD-transformer	8%	3%	7%	2%
TRAD-cable	60%	89%	65%	91%
TRAD-transfer load	6%	2%	4%	1%
TRAD-new feeder	1%	2%	1%	2%

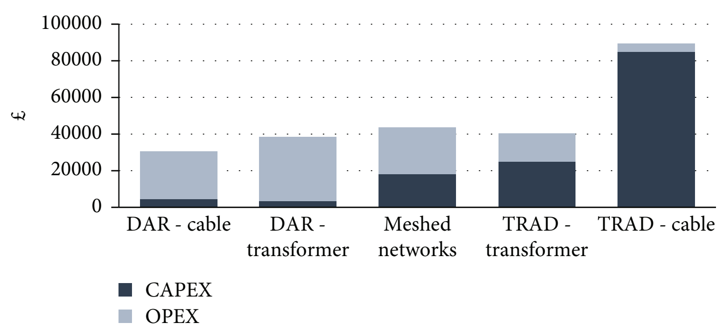

Figure 11: Average cost disaggregation per technique; DECC4, 2015–2023.

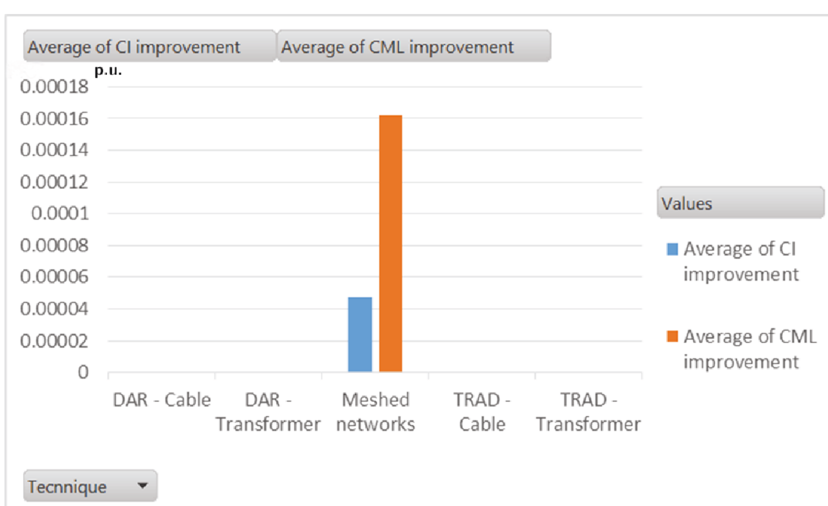

Figure 12: Average CML and CI improvement per technique; DECC4, 2015–2023.

solutions for DECC4 and DECC2, as described in Table 2. These three techniques applied are DAR for cables and transformers and meshed networks.

Comparing the cost trends of the two assessed scenarios, it is notable that in both demand scenarios, DECC4 and DECC2, the CAPEX peak occurs in 2015 (Figures 9 and 13), reflecting the more difficult nature of network states to be feasible in a demanding scenario, whereas DECC2 shows a higher improvement of CI and CML performance indicators as can be seen in Figures 10 and 14.

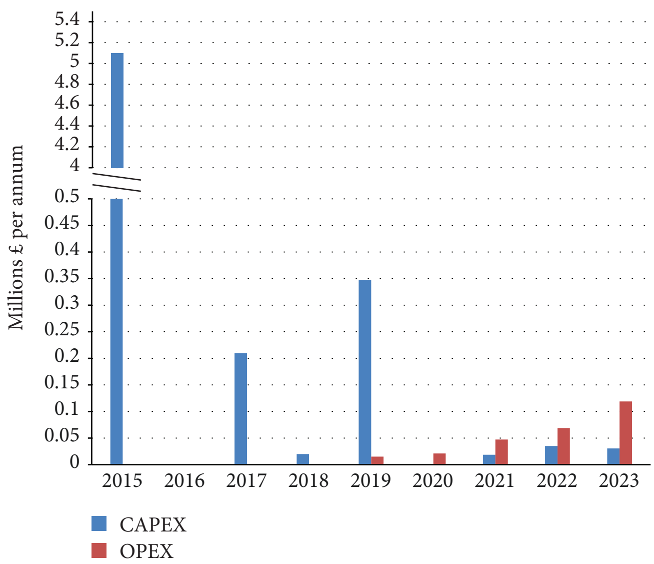

FIGURE 13: CAPEX and OPEX; DECC2, 2015–2023.

The techniques applied are the key consideration to be assessed. It is necessary to analyse the number of interventions applied by type, the effect of these techniques in the electric grid solving failures and fixing assets. Figures 11 and 15 show average prices of techniques used in each demand scenario. Smart techniques have a lower TOTEX than traditional reinforcements. These novel techniques above are not frequently able to fix failures and therefore produce feasible network states. In terms of CML and CI, the only technique able to moderately contribute to their improvement is meshed networks as shown in Figures 12 and 16. Results attribute the majority of fixes to traditional reinforcements with a comparatively smaller number of failures being solved by smart techniques (Table 2). The results obtained in terms of traditional reinforcement share for 2015–2023 show a 60% proportion of intervention for DECC4 and a 65% proportion of intervention for DECC2, which is close to the 59% forecasted by the transform model for this evaluation period.

For DECC4, the three mentioned techniques along with traditional cable and transformer replacement are applied (Table 2), whereas for DECC2, two of them are applied, DAR for cables and meshed networks (Table 2). Comparing the cost trends of the two assessed scenarios, it is notable that in DECC4, the CAPEX peak occurs in 2015 (Figure 7), whereas in DECC2, besides the peak in 2015, there is also one in 2019 (Figure 11), reflecting the more difficult nature of network states to be feasible in a demanding scenario. However, DECC2 shows a higher improvement of electrical performance indicators as can be seen in Figure 12.

In addition, traditional cable replacement, DAR for cables, and meshed networks are able to fix the cable, whereas traditional transformer replacement and DAR for transformers are able to fix transformer issues (Figure 16). The results obtained in terms of traditional reinforcement share for 2015–2023 show a 60% proportion of intervention for DECC4 and a 65% proportion of intervention for DECC2, which is close to the 59% forecasted by the transform model for this evaluation period.

4.2. Long-Term Planning. This section evaluates two experiments, namely, characterising the DECC2 and DECC4 scenarios for 2015–2047 evaluation period. For each demand scenario, expected investments disaggregating CAPEX and OPEX are presented, the evolution of electrical performance indicators and the number of techniques applied.

4.2.1. DECC4, 2015–2047. In this experiment, the most significant results to analyse the suitability of each technique are presented.

Figure 17 shows the trend of CAPEX and OPEX from 2015 to 2047.

There are CAPEX peaks in the year 2018 and during the beginning of RIIO-ED2 in the years 2025 to 2026, due to the application of more techniques to fulfill low-carbon targets.

Figure 18 indicates that upgrades on the network are directly related to technical performance indicators, CML and CI.

In Table 3, the techniques applied and their contribution to CAPEX during the evaluation period from 2015 to 2047 by a demand scenario are shown.

4.2.2. DECC2, 2015–2047. Within this experiment, the most relevant results to analyse the evolutionary network states are presented.

In Figure 19, the trend of CAPEX and OPEX from 2015 to 2047 is shown. There is a significant increase of CAPEX in the years 2024 to 2026 at the beginning of RIIO-ED2, due to the necessary implementation of new techniques to reach low-carbon targets. The evolution of CML and CI is presented in Figure 20, linking larger investment years when major reductions are found. The contribution of each solution technique is presented in Table 3.

4.2.3. Comparison between DECC2 and DECC4 for 2015–2047. Figure 21 presents a multidimensional parallel coordinate representation of the feasible network state's combinations that produced a 2015–2047 investment pathway for the evaluated area. It bundles economic indicators, i.e., CAPEX and OPEX, with technical performance indicators providing valuable insights on the number of traditional reinforcements utilised to heal falling network states. Results are also clustered by the two demand scenarios assessed during the experiments.

Solutions of DECC2 (represented in orange and green) and DECC4 (in black and blue) are clustered by the percentage of traditional reinforcements utilised as well as the utilisation factor.

Solutions in green and in black represent those where smart grids were more used, whereas orange and blue represent the cheapest (CAPEX and OPEX), less utilised, and the worst responding to the decrease of CML, CI, and losses, and the ones using more traditional reinforcement to fix network states.

Besides the fact that DECC2 smart solutions are between 16% and 28% more expensive than DECC4 traditional

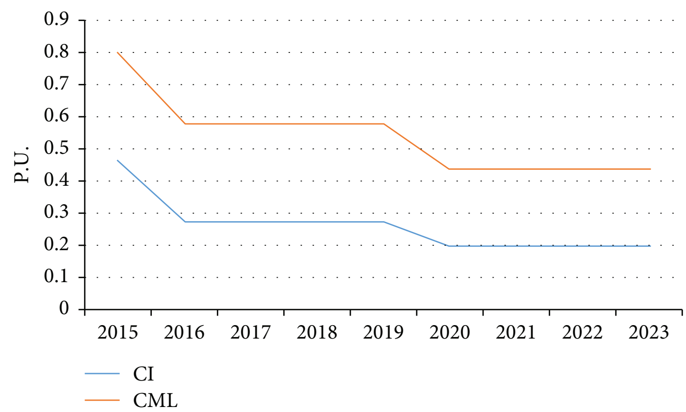

FIGURE 14: CML and CI; DECC2, 2015–2023.

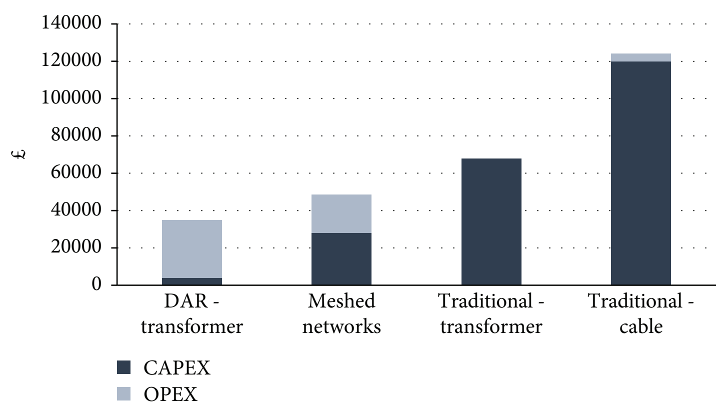

FIGURE 15: Average cost disaggregation per technique; DECC2, 2015–2023.

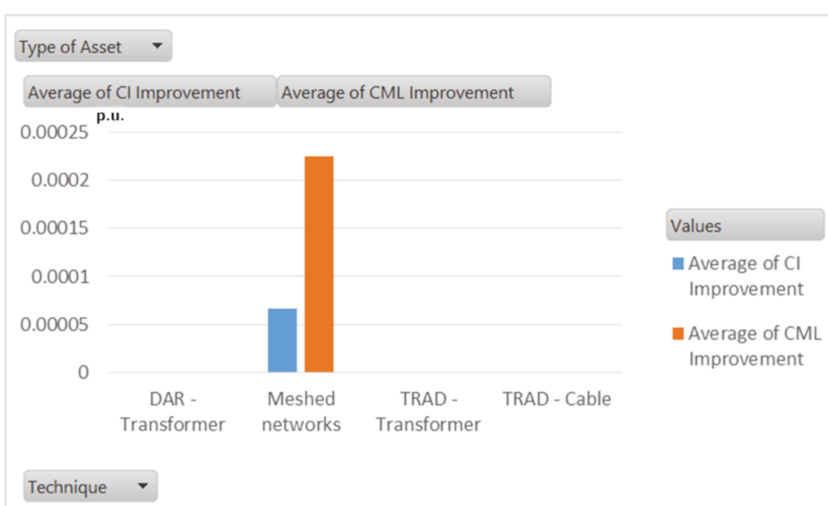

FIGURE 16: Average CML and CI improvement per technique; DECC2, 2015–2023.

reinforcement solutions (green solutions versus blue solutions in Figure 21), DECC2 traditional solutions are in the range of costs of smart solutions of DECC4 (orange and black solutions in Figure 21). It can also be concluded that investment pathways using less smart techniques provide a cheaper response to technical performance evaluators such as utilisation, CML, CI, and losses.

4.3. Summary. Experiment evaluation runs from the 2015–2047 period present lower investment rates for the

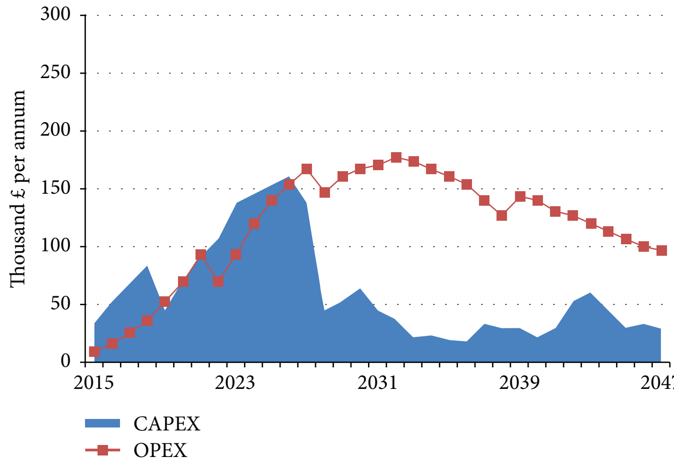

Figure 17: CAPEX and OPEX; DECC4, 2015–2047.

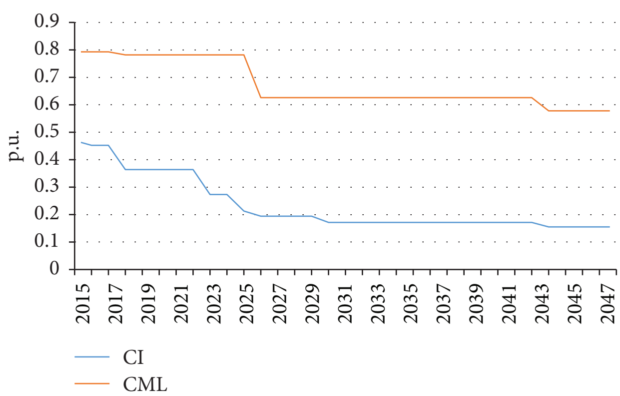

Figure 18: CML and CI; DECC4, 2015–2047.

2015–2023 period than if the evaluation is just performed with a 2015–2023 time frame. This occurs as a result of the challenging low-carbon targets up to 2047 and a myopic planning with short-term lookahead. For an evaluation period four times larger, the CAPEX and TOTEX increased just 18% compared to 2015–2023, concluding that between £5.2M and £6.8M, the evaluation area regardless of the time horizon for the investment or the demand scenario considered is required.

Furthermore, it can be inferred comparing Tables 2 and 3 that for less smart interventions, the short-term planning is used compared to the long-term horizon planning. DAR-cable and DAR-transformer experienced a significant implementation variation between the two evaluation periods for both demand scenarios, as well as CAPEX allocated in cable upgrades falling from 89–91% (2015–2023) to 29–66% in the long term 2015–2047 run. Both technical performance evaluators, CML and CI, respond to their respective CAPEX curve shape. Due to a more incentivised smart grid technique during RIIO-ED2 and ED3, the percentages of smart techniques implemented varied notably. For DECC4 in 2023's outlook, the share of techniques is 25% for smart grid interventions whereas for 2050's outlook, the share is increased up to 58%. In the same way for DECC2 in 2023's outlook, the share of smart interventions is 23% whereas in 2050's outlook, the share increases up to 69%.

Feasible solutions characterising the solution space (Figure 21) differ in the degree of investment required and technical performance evaluators. Each of the solution path represented in the multidimensional solution space in Figure 21 represents the intersection of that dimension with each axis. Parallel coordinates [35] are low complexity working for any N-dimension. In the case of Figure 21, it has 8 dimensions, treating every variable uniformly. Each intersection of one solution path with each axis is the value of that solution for that axis. As for axis DECC2 and DECC4, it represents the feasible solutions for each demand scenario. Making a query by the percentage of traditional reinforcement used in that solution, we have the partition between orange and green for DECC2 and blue and black, being the first solutions that use more traditional reinforcement compared with the ones that use more smart techniques represented in green (DECC2) and black (DECC4). From Figure 21, we can argue that solutions that use more smart techniques (green and blacks) are more expensive in terms of CAPEX and OPEX than their peers (orange and blues) when compared by a demand scenario. It can also be stated that solutions with a higher use of traditional reinforcements are the ones that decrease the most, CML, CI, and losses.

Disaggregating results by network state of the six 11 kV primaries and by the feeder, if necessary for further granular debugging, can discern locational capacity. Under both demand scenarios, Secklow Gate was seen to be the one with greater capacity, being necessary to apply fewer techniques over the evaluation period, 2015–2047. On the other hand, Newport Pagnell exceeds the capacity as soon as 2015, requiring a high number of network state evaluation to be fixed that happens for each subsequent year; hence, the large number of network states is presented in Table 4.

Table 3: Number of interventions and CAPEX involved; DECC4 and DECC2, 2015–2047.

Technique	DECC4 Proportion of interventions (%)	DECC4 CAPEX (%)	DECC2 Proportion of interventions (%)	DECC2 CAPEX (%)
DAR-cable	18%	5%	31%	6%
DAR-transformer	32%	16%	32%	6%
ALT	0%	0%	0%	0%
Mesh	8%	3%	6%	3%
Batteries	0%	0%	0%	0%
DSM	0%	0%	0%	0%
DG	0%	0%	0%	0%
TRAD-transformer	25%	44%	9%	16%
TRAD-cable	15%	29%	20%	66%
TRAD-transfer load	1%	1%	1%	1%
TRAD-new feeder	1%	2%	1%	2%

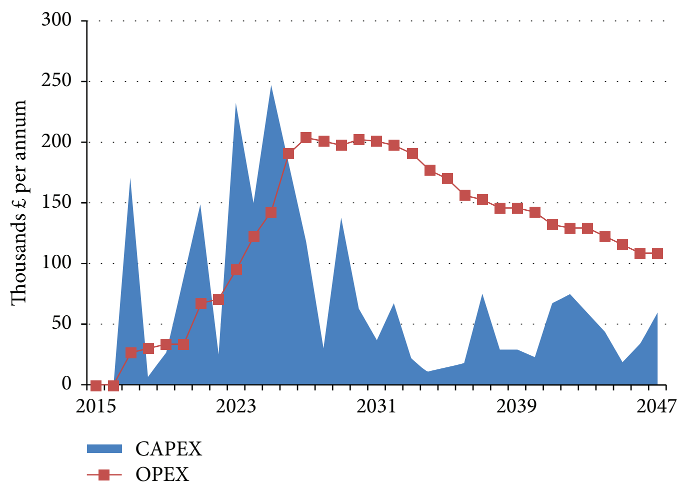

Figure 19: CAPEX and OPEX; DECC2, 2015–2047.

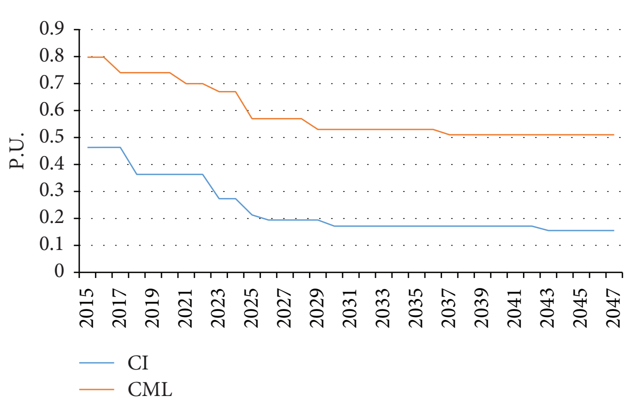

Figure 20: CML and CI; DECC2, 2015–2047.

5. Conclusions

Power flow analysis using a nodal network model is essential when determining the benefits of trailed smart interventions because the interactions and implications are highly specific to a particular location and scenario.

This suggests that while the bottom-up approach is onerous in terms of data handling and manipulation, this is worthwhile for strategic planning and policy evaluation. Comparing both investment strategies, investment strategy adjustments will be necessary in future regulation periods if an over-invested network behaves as displayed in the short-term section of this study.

Traditional reinforcement will continue to be the main method by which network issues are mostly resolved, followed by dynamic asset rating and meshed networks.

The assessment of the six novel smart interventions in the FALCON 11 kV primary test area in Milton Keynes has proved the suitability of three techniques able to fix failures, improving the quality of service, and their readiness to be deployed in the near future. These techniques are DAR for cables and transformers and meshed networks. Meshed networks have been repeatedly selected as a feasible technique because using it will reduce CML, CI, and power losses,

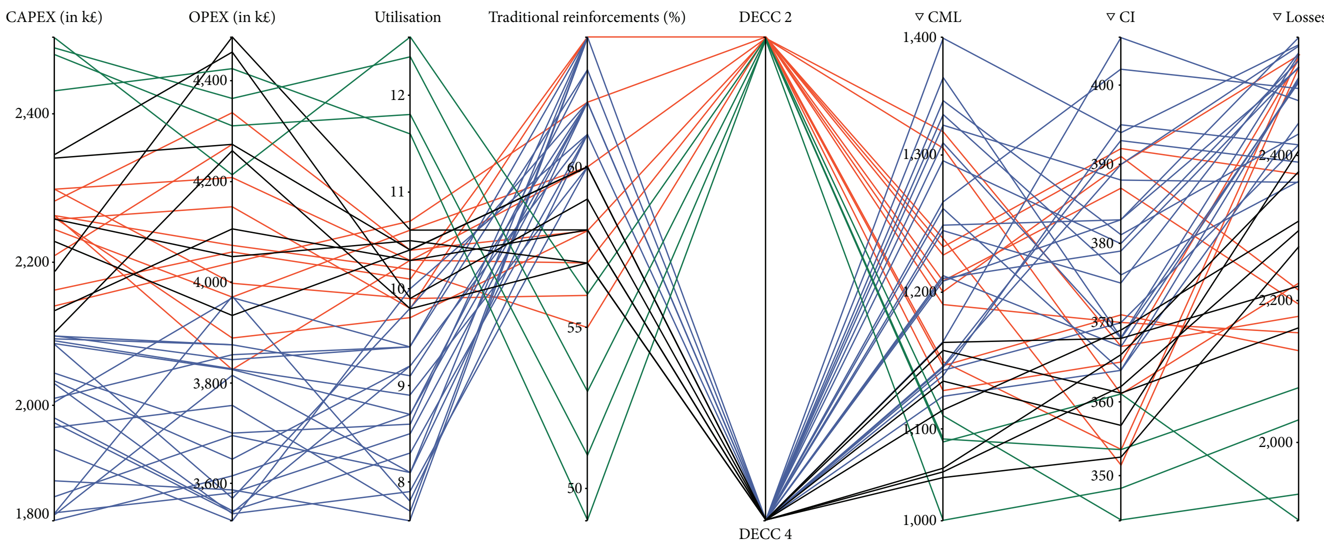

Figure 21: Parallel coordinate visualisation of technoeconomic performance indicators under DECC4 and DECC2.

Table 4: Summary of network states and results for demand scenario; DECC4 and DECC2.

Primary 11 kV substation	Feeders	Year	Techniques	Results DECC4	NS DECC4	Results DECC2	NS DECC2
Fox Milne	13	2047	Smart and traditional	54	276	47	259
Newport Pagnell	9	2047	Smart and traditional	48	317	31	318
Secklow Gate	9	2047	Smart and traditional	27	29	15	16
Bletchley	19	2047	Smart and traditional	32	40	21	48
Marlborough Street	11	2047	Smart and traditional	31	52	19	37
Childs Way	17	2047	Smart and traditional	67	398	54	181

improving the quality of service and the efficiency, while being a cost-effective solution.

The initial capacity at primary substations differed significantly, and this affected the number and complexity of interventions required by the SIM. Due to the load scenarios showing significant peak load increases, DAR was often a temporary measure that would delay but not remove the eventual need for traditional reinforcement.

Implementing DAR for cables and transformers, the monitoring of assets when their peak capacity is increased was analysed. On the other hand, it was observed that traditional reinforcements still play a key role in keeping the electricity distribution networks free of constraints. TRAD techniques such as transformer and cable replacements are able to fix the majority of failures and will be essential also in the future.

The comparison between traditional reinforcements and novel smart techniques has provided a new knowledge about the suitability of each technique to be applied, in terms of costs, electrical performance, failures fixed, and asset replaced. Cable replacement is the most costly technique; however, its use is unavoidable in a number of cases. Furthermore, the applicability of each technique regarding costs involved, improvements on power quality and efficiency, and failures solved lead to new questions to be analysed, such as the lack of these techniques to provide flexible capacity within the trailed area.

To sum up, this study has performed a comparative analysis of novel smart intervention techniques, providing insights for future investments in electricity distribution planning. Further work can focus on scaling up the analysis to include a larger section of the network or a constrained area to evaluate national applicability of the current findings.

Data Availability

Some of the data relevant to this submission is proprietary from Western Power Distribution. It can be accessed for research purposes under a signed collaboration agreement.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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Technoeconomic distribution network planning using smart grid techniques with evolutionary self-healing network states

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